

# Bursty egocentric network evolution in Skype

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In this study we analyze the dynamics of the evolution of the contact lists of millions of users of the Skype communication network. We find that egocentric networks evolve heterogeneously in time as edge additions and deletions of individuals are grouped in long bursty clusters. We classify users by their contact addition dynamics and show that bursty peaks of contact additions are likely to appear shortly after user account creation. We also study possible relations between contact addition activity and other user-initiated actions. Evidence is put forward that bursty peaks in contact addition are associated with both free and paid service adoption events.

## I. INTRODUCTION

The structure and evolution of human interactions are generally characterized by heterogeneity in manifold ways and are influenced by several correlations ranging from individual level to global scale [2, 4, 7, 22, 28]. Some of these emerging heterogeneities have been identified as the result of simple processes driven by microscopic rules. For example, preferential attachment [26] has been shown to introduce degree heterogeneity and short pathways into an evolving network structure, while affinity of local triangle closing [19] induces high clustering coefficient and largely overlapping neighborhoods leading to strongly modular network structures. At the same time studies of action sequences – such as communication actions in social networks – have put into evidence further mechanisms responsible for inhomogeneities in network structure and dynamics [12, 15, 24]. It has been shown in particular that communication and topology are not independent, enhancing the importance of weak ties linking communities [25] and that correlated dynamics of individuals induce bursty temporal patterns of interactions [13, 14, 16, 27]. However, for the most, these studies draw their conclusions from observation of static network snapshots or from incomplete temporal sequences of interactions. Only recently it has become possible to follow the dynamics of large-scale networks at the microscopic level as a number of datasets have been collected that contain time-stamped records of all topological actions, such as addition and deletion of edges between pairs of users [1, 6, 19]. This development has opened the possibility to study directly the governing microscopic rules of network evolution in order to confirm previous hypothesis and to explore new mechanisms.

In particular, the availability of time-stamped records of user registrations, edge additions and edge deletions, allows to explore in details the microscopic evolution of *egocentric networks*, where an egocentric network consists of an individual user and their immediate friends or “con-

tacts”. The observed evolution of such microscopic networks can be the aggregation of several processes. Creating a link could be the result of finding an old friend who is already in the network, but could be also a sign of real emergence of a new relationship. Sudden dramatic changes in the egocentric network could be induced by changes in the ego’s social status (e.g. moving to a new place or starting a school) but also by the adoption of new services which open possibilities for alternative ways of interactions.

In this study we characterize the temporal evolution of egocentric networks in a very large online social network. We present for the first time empirical results on a dataset that contains anonymized data of hundreds of millions of subscribers of Skype – one of the largest world-wide online communication system available. We mainly focus on the temporal evolution of trusted social links of individuals and we detect correlated bursty periods in their edge addition and deletion dynamics. We also highlight some possible reasons behind bursty behaviour by looking for correlations between the observed dynamics and other user-initiated actions. To study these phenomena is not only important because we gain deeper understanding into technology-enabled human behaviour but also because it provides us insights to design better services and to optimize computational resources.

The rest of the paper is structured as follows. In the Section II we give a brief description of the utilized datasets which after in Sections III and IV we present our main results about the temporal evolution and correlations of egocentric networks. In Section VI we overview the related works reported in the literature and finally in Section VII we summarize our main findings.

## II. DATA

This research is based on a dataset consisting of a temporally detailed description of the social network of (anonymized) Skype users. For each user, the dataset provides the following details:

- Date of registration of the user

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- For each type of paid service (e.g. PSTN calls), date when the user first and last used this service (whenever applicable).
- Time series indicating the number of days in each month when the user connected to the Skype network
- For each type of free service (e.g. Skype-to-Skype audio calls, video calls, chat, etc.), time series indicating the number of days in each month when the user used this service.

Additionally, the dataset comprises user connections. In the Skype network, when a user adds a friend to his/her contact list, the friend may confirm the contact invitation or not. Also, at any point in time a user may delete a “friend” from their contact list.[?] ] Thus, the network evolves by means of the following events: contact addition, contact confirmation and contact deletion.

In order to take into account only trusted social links we retained only confirmed edges, meaning edges where both parties accepted the connection. Failure to do so would lead to mixing undesired with desired connections.

For the present study we employed two subsets of the above dataset. The first dataset (DS1) includes every active user as of the end of 2010, all confirmed edges between these users, and the date of confirmation of each edge. In this context, we define an active user as one who connected to the Skype network at least in two different months during the first year after their registration date. In order to consider users with realistic number of friends we selected only those with degree between 2 and 1000. This filtering led to a set of more than 150 million users.

The second dataset (DS2) included the complete set of edge addition, edge confirmation and edge deletion events recorded for a year-long period in 2010 – 2011. Only events related to users with degree between 2 and 1000 were kept. Unlike DS1, non-active users were retained in DS2.

### III. EGOCENTRIC NETWORK EVOLUTION

In this section we look at the evolution of egocentric networks to gain deeper understanding about the governing microscopic rules of contact list evolution.

#### A. Bursty edge dynamics

To characterize the temporal evolution of contact lists, we first look at the edge addition and deletion sequences of individuals and calculate the distributions of inter-event times

$$\tau_a = t_{i+1}^a - t_i^a \quad \text{and} \quad \tau_d = t_{i+1}^d - t_i^d \quad (1)$$

elapsed between consecutive additions at  $t_i^a$  and  $t_{i+1}^a$  or deletions at  $t_i^d$  and  $t_{i+1}^d$  of the same user. If this distribution is broad and follows a power-law as

$$P(\tau) \sim \tau^{-\gamma} \quad (2)$$

it indicates strong temporal heterogeneities and burstiness, or otherwise if it decays exponentially it reflects regular dynamical features. Bursty temporal evolution of human dynamics was confirmed in various systems ranging from library loans to human communication [7, 14] or recently for the evolution of social networks [6].

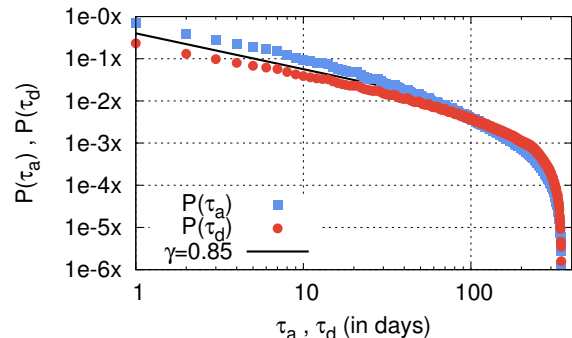


FIG. 1. Inter-event time distributions of edge addition (blue squares) and deletion (red circles) events of users in DS2. The straight line indicates a power-law function with exponent  $\gamma = 0.85$ .

Calculating  $P(\tau)$  for DS2 we observe broad inter-event time distributions both in case of edge additions and edge deletions. The distributions are showing rather similar scaling with a broad section fitting on a power-law with exponent  $\gamma \simeq 0.85$  and an exponential cutoff due to the finite time window. This is an interesting observation as one would expect rather different decision mechanisms behind adding and deleting a contact. However, the similarity of the two distributions indicates common temporal features and bursty dynamics both in case of edge addition and deletion.

#### B. Trains of bursts

The broad inter-event time distribution is indicative of the presence of heterogeneities, however it cannot show whether further correlations are present between consecutive actions. Recently a new methodology was developed [13] to address this question and evince evident correlations in heterogeneous binary signals. It counts the number of consecutive events which follow each other with inter-event times smaller or equal to  $\Delta t$ . The sensitive measure of correlations serves as the  $E$  number of events in bursty clusters as its distribution scales as a power-law

$$P(E) \sim E^{-\beta} \quad (3)$$

if the signal is correlated and long event trains are evolving in the dynamics. On the other hand if consecutive events are independent it decays exponentially even the inter-event time distribution is fat-tailed.

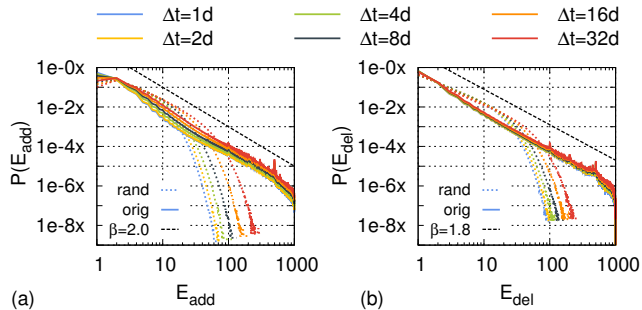


FIG. 2. Distribution of number of events in bursty trains of (a) contact addition and (b) deletion of individuals in DS2. Distributions were calculated with time window sizes  $\Delta t = 1, 2, 4, 8, 16$  and  $32$  days. Distributions calculated for randomly shuffled sequences are also presented (dashed line) calculated with the same  $\Delta t$  values. Straight lines are indication of power-law functions with exponents (a)  $\beta = 2.0$  and (b)  $\beta = 1.8$ .

In the present case we analyzed the edge modification sequence of each individual, we detected the clusters of events of new edge addition and deletion and record their size  $E_a$  ( $E_d$ ). The broad  $P(E_a)$  and  $P(E_d)$  distributions in Fig.2 confirm the presence of correlations evolving between consecutive events of edge additions (deletions) as the corresponding train sizes are distributed as a power-law with characteristic exponent values  $\beta_a \simeq 2.0$  ( $\beta_d \simeq 1.8$ ). This scaling behaviour appears to be robust against the selection of the  $\Delta t$  window size as it remains similar for distributions calculated with  $\Delta t = 1, 2, 4, 8, 16$  and  $32$  days.

The presence of correlations in the egocentric dynamics are even more apparent if we compare the empirical  $P(E)$  functions to the equivalent distributions calculated for independent signals. To receive a reference system like this we used the  $\tau_a$  ( $\tau_d$ ) inter-event times of the original sequences, put them in a pool and redraw for each user randomly as many inter-event times as they had originally. The inter-event time distribution of the resulted randomly shuffled null model was similar to the original  $P(\tau)$  distribution as we used the same  $\tau_a$  ( $\tau_d$ ) values and also the shuffled sequences of each user contained the same number of events as before. However, with this random shuffling method we destroyed all possible temporal correlations which were present between the consecutive events of single users. The  $P(E)$  distribution of such random shuffled sequences should decay exponentially [13] and any discrepancy from this scaling behaviour is indicative of correlations.

It is demonstrated in Fig.2.a and b that the  $P(E)$  distributions calculated for the randomly shuffled reference sequences (dashed lines) are exponentially distributed and they are very different from the original distribu-

tions (solid lines). It puts into evidence that the actions of an individual are not independent and we can conclude that the evolution of egocentric networks is not only heterogeneous in time but intrinsic correlations are driving its dynamics. They lead to the evolution of high activity bursty periods, where a large number of edges are added or deleted, and which are followed by long low activity intervals.

#### IV. GROUPS OF INDIVIDUAL DYNAMICS

So far we have observed that edge addition and deletion events of an individual are bursty and clustered in time, yet we know less about when these bursty trains are evolving during the lifetime of a user. Do they appear in any time or there are typical activity patterns of edge additions or maybe triggered by other user actions? In the following we address these questions by seeking correlations of bursty peaks with other user activities.

In order to compare the edge addition sequences of individuals we used DS1 and concentrated only on the activity of users during the first year of their  $t_u$  user time i.e. the time after their registration. We were keeping track the  $a_i$  number of newly added edges of each node  $i$  with a single month resolution and receive a discrete  $a_i(t_u)$  sequence for each individual where  $t_u = 1 \dots 12$ . To be able to compare sequences of users with diverse overall intensity we applied the *Symbolic Aggregate Approximation* [20] method with alphabet size 10. Other methods e.g. combining standardization with *Discrete Wavelet Transform* [3] were tested and served very similar results (not shown here). To detect groups of users with similar edge addition dynamics we applied the *k-means clustering* [9] method on the activity sequences using euclidean distance. It has been shown that running k-means on data that was previously processed by SAX produces better results than the original data [21]. To choose the number of clusters we applied the clustering for different values up to 200 clusters and determined that the sum of squared errors levels off at some point where  $k > 40$  (the approach is also referred as *Elbow method*). After inspecting different clusterings manually, we determined  $k = 44$  to be around optimal. K-means algorithm was chosen for its ability to scale to  $O(100M)$  data points. The aim here was to use clustering to exploratory analyze the data and not to find single clustering and therefore we decided not to imply formal model selections methods.

In Fig.3 we show the  $\langle a_i(t_u) \rangle_k$  average activity curves of each  $k$  cluster together with the percentage of users who are belonging to the actual group. Looking at the most common patterns it is straightforward that typically people perform their principal (the largest and usually the only one) edge addition burst right after they join the network. This is the time when they explore their social acquaintances who have already joined Skype before and which after they add contacts just occasionally with lower

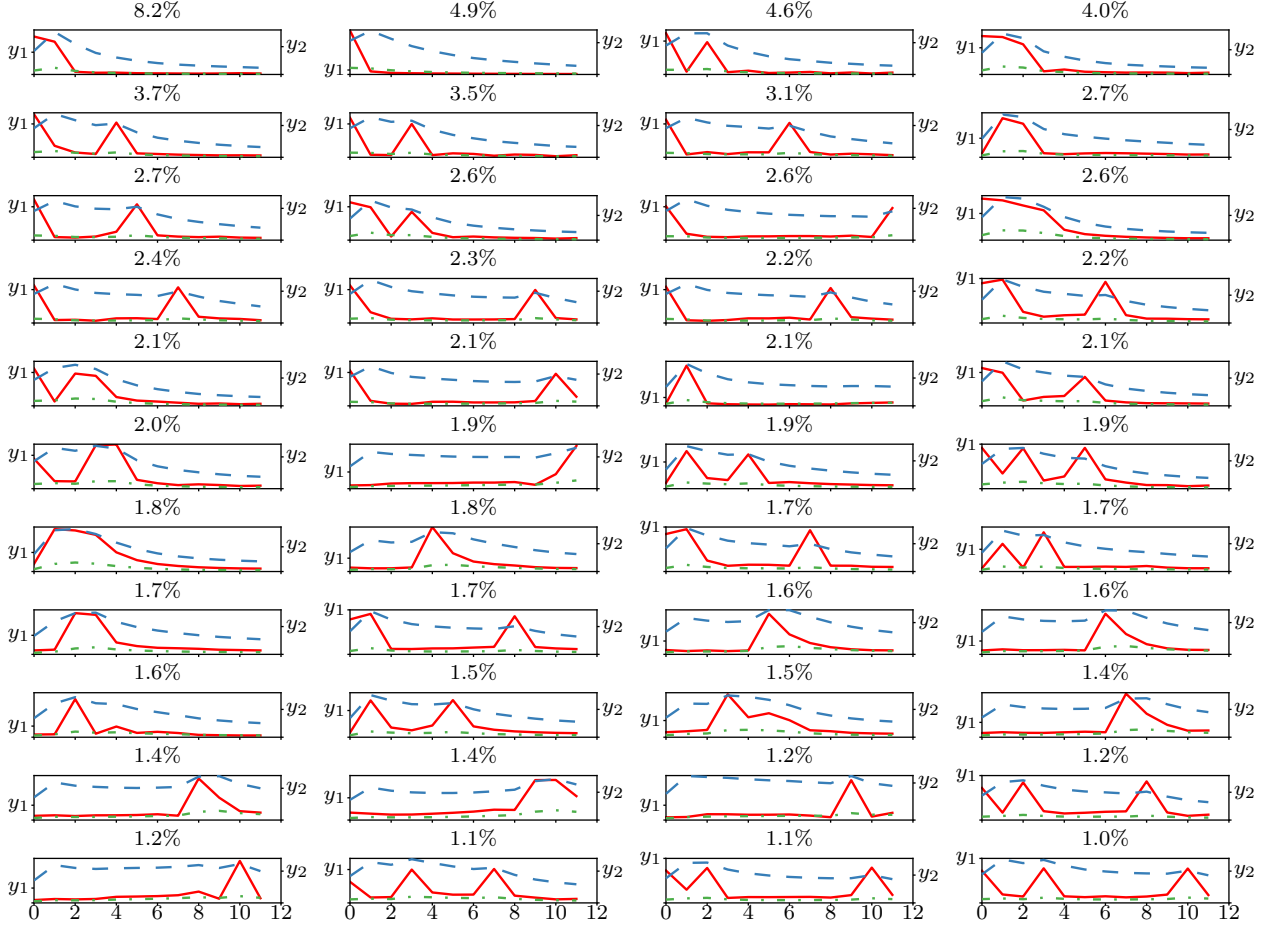


FIG. 3. Characteristic groups of contact addition patterns calculated for DS1. On each panel red solid lines correspond to the average number of new contacts added at the actual month, dashed blue lines are the average number of connected days, while green pointed lines are the average number of days used Skype-to-Skype communication belonging to the actual group. Clustering is obtained by clustering only contact addition (red line). Panels are in descending orders regarding the partition of users they cover (percentage above each panel). Left scales corresponds to the number of added contacts while right scales are number of days. The tick with label  $y_1$  ( $y_2$ ) on the left (right) vertical scale is corresponding to the same value on each panel.

frequency. This behaviour is confirmed by looking at the  $\langle a_i(t_u) \rangle$  average number of new edge additions (Fig.4.a) calculated for each user. Note that a similar behaviour was observed in other studies [6]. In addition, Fig.4.b shows that this correlation is independent from the time of registration as similar early stage peaks were found for users who joined Skype at different years.

To check the significance of this phenomenon we compare the  $\langle a_i(t_u) \rangle$  overall average curve to a similar curve  $\langle a_i(t_u) \rangle_r$  calculated for independent sequences. To generate the null model sequences we apply a very similar method as earlier. We take the activity values of each user at each month, randomly shuffle them and redistribute between users. This way the overall activity remains unchanged and each user have a sequence of 12 data points as before, but the correlations between activity peaks and user time are destroyed. The resulting average activity curve becomes flat evidently as it is

demonstrated in Fig.4.a (blue line). Comparing the original and random curves (red and blue lines in Fig.4.a) it is straightforward that the peak at early times, which is visible for the original curve, is not observable for the null model curve supporting the significance of the correlation.

## V. CORRELATIONS AT LATER TIMES

A single bursty peak at early time is not the characteristic of every user. Less common motifs in Fig.3 show that principal bursts may emerge later or even in multiple times. This observation indicates that events other than user registration may also trigger immediate changes in the egocentric network. Changes in social status as moving to another place or starting school could be possible reasons behind the later bursty peaks, but given

	S2S	activ	S2S rand	activ rand
$\langle r \rangle$	0.34608	0.308137	8.31909e-6	1.69978e-5

TABLE I. Average correlation coefficient calculated between edge addition dynamics-free service usage (S2S) and connected days (activ). Values received for random sequences are also presented.

the actual dataset, we are not in a position to confirm these effects. However, it is possible to study dependencies between the dynamics of contact addition and other system-related activities.

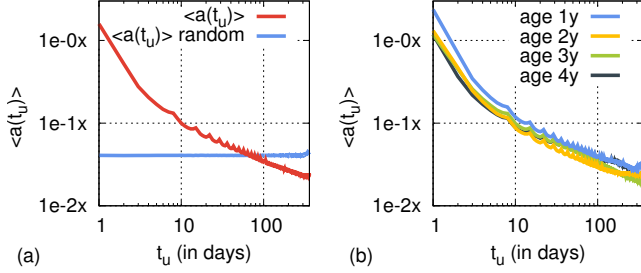


FIG. 4. Average number of new contacts added as function of  $t_u$  user time calculated for (a) all users in DS1 and (b) for users grouped by the time they joined Skype. Age in the (b) figure caption refers to the time of registration in advance of the measurement.

In Fig.3 besides the average edge addition rates we also show the average number of connected days and average number of days of free-service usage for each group. Comparing these curves one can foresee some dependency between them as users are performing bursty contact addition months at the time when they are connected and also heavily using free services. To quantify these relationships we calculated a correlation coefficients for each user  $i$  defined as

$$r_i^s = \frac{\langle (a_i(t) - \bar{a}_i)(s_i(t) - \bar{s}_i) \rangle_t}{\sigma_{a_i} \sigma_{s_i}} \quad (4)$$

where  $s_i(t)$  denotes the sequence of number of connection days or free service usage days and the average is running through 12 discrete time steps. The  $CDF(r)$  cumulative distribution of the two coefficients calculated for every users is depicted in Fig.5 (dark red curve for correlations with Skype-to-Skype free services (S2S) and dark blue curve with connected days (activ)). They indicate mostly positive correlations as almost no user was found with coefficient  $r \leq -0.5$  and at the same time approximately 80% of users present non-negative correlations in both cases. The  $\langle r \rangle$  average correlation coefficients of the two distributions assign also strong positive correlations as they take values  $\langle r_{S2S} \rangle = 0.34608$  and  $\langle r_{activ} \rangle = 0.308137$  for the free service and user activity accordingly (vertical dashed lines in Fig.5).

To check whether the observed positive correlations are significant or only the results of random fluctuations

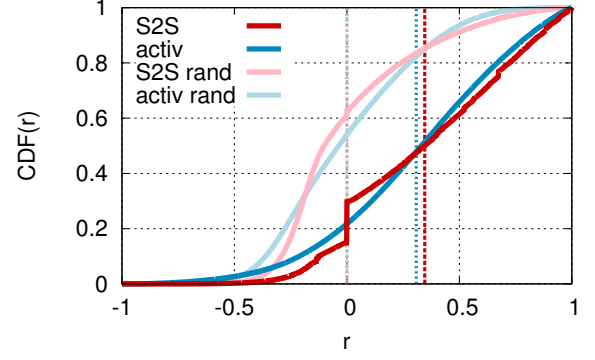


FIG. 5. Cumulative distribution of the  $r$  Pearson correlation coefficients calculated between the contact addition dynamics of individuals, their service usage intensity and user activity during their first  $t_u = 12$  months (solid dark red and blue lines accordingly). Similar curves calculated for random sequences are also shown (solid light red and blue accordingly). Dashed vertical lines assigns the average correlation coefficient  $\langle r \rangle$  of the present distributions (for numerical values see Table.I).

of independent processes we calculated the correlations between the same curves but after we randomly shuffled the activity sequences. To generate the null model sequences we applied the same method described above in Section IV for each sequences. The cumulative distribution functions of the correlation coefficients calculated between the random sequences are shown in Fig.5 (light red line for free service usage and light blue line for user activity). These curves are very different from the ones of original sequences and also their average values are presenting significant discrepancies. For random sequences  $\langle r_{S2S}^{rand} \rangle \simeq \langle r_{activ}^{rand} \rangle \simeq 0$  in agreement with the expected values of correlations calculated between independent signals (the average values for all calculated  $CDF(r)$  are summarized in Table I). Consequently the observed dependencies between the original sequences are significant and they indicate true positive correlations between the edge addition dynamics of individuals, their user activity and free service usage.

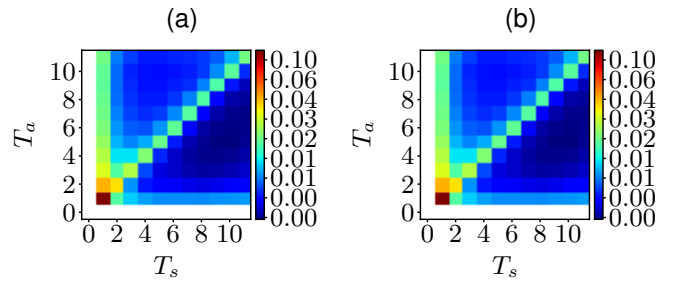


FIG. 6. Matrices of conditional probabilities that a user performed a peak contact addition month at  $T_a$  if he adopted a (a) free or a (b) paid service at  $T_s$ . Probability values at  $T_a = 0$  and  $T_s = 0$  are not shown. Colors are coding logarithmically the probability values.

Another possible reason behind sudden changes in the egocentric graph can be due to the adoption of a new communication service which opens an alternative way of interaction. This channel could be a free communication service what the user explored or could be a paid service what he/she subscribed for. Therefore, one can look for the time when a user starts to use a free or paid service for the first time and check whether these actions can trigger bursty peaks in contact addition. To do so we identify bursty peak months for each user as the months where the contact addition activity is

$$a_i^p(t) = (a_i(t)|a_i(t) \geq \bar{a}_i + 2\sigma_{a_i}). \quad (5)$$

Here  $\bar{a}_i$  and  $\sigma_{a_i}$  denotes the average and standard deviation of the contact addition activity sequence of user  $i$ . In Fig.6.a and b we present the conditional probabilities that a user performs a peak month of contact addition at a given user time  $T_a$  if he/she adopted a free (Fig.6.a) or a paid service (Fig.6.b) at time  $T_s$ . We have seen earlier that strong correlations are playing role between the user activity and registration time at  $t_u = 0$ . However, here we are looking for correlations which evolve later in user time. To avoid the dominating effect of strongly correlated early activity peaks in Fig.6 we neglect the data bins belonging to adoption time  $T_s = 0$  and bursty peak time  $T_a = 0$  and normalize the probabilities accordingly. After this preparation, correlations between late service adoption and peak contact addition months became visible as a high activity diagonal appeared in the probability matrices in Fig.6.a and b. Consequently together with correlations with registration and user activity this result serves us another possible explanation for the late evolution of bursty contact addition peaks as they are possibly triggered by paid or free service adoption.

## VI. RELATED WORK

Temporal evolution of networks was studied thoroughly during the last years as datasets recording the dynamics of millions of interacting entities became available [10]. One of the most investigated area was the evolution of large social networks [8, 17, 18, 25] where it has been shown that several mechanisms push such networks towards developing heterogeneous topologies and strongly modular structures [1, 19, 26]. In addition various methodologies have been developed to detect evolving mesoscopic patterns [16, 23] and emerging community structures [5]. Our study falls under the same umbrella as these previous works but focuses on the temporal evolution of egocentric networks.

Heterogeneities in the dynamics of social interactions have been observed by following the communication sequences of individuals [2, 4, 7, 22, 28]. Circadian fluctuations and long range temporal correlations were shown to play important role here [11, 13, 14, 27] and they partially explain the observed non-homogeneous behaviour. Lately heterogeneous evolution of social networks was

also reported by Gaito et al [6] who analyzed the dynamics of the Renren online social network. In this paper Gaito et al [6] simultaneously arrived to similar conclusions as us as regarding the burstiness in the evolution of contact addition of users. In our study – beyond confirming this effect in an independent dataset – we extend this finding in two ways. First, we put forward evolving bursty trains also in the sequence of contact deletion of individuals and second we highlight non-trivial correlations triggering bursty periods in the evolution of egocentric networks.

## VII. CONCLUSIONS

Our motivation in this study was to understand the temporal evolution of egocentric networks in an online environment as looking for the contact modification dynamics of individuals. We investigated for the first time one of the largest online social network currently available, the network of Skype users. Our main observation was that the dynamics of edge addition and deletion show strongly heterogeneous temporal behaviour as most of the edges are added or deleted during very short bursty periods which are separated by long low activity intervals. During such high activity periods long bursty trains of contact addition events can evolve confirming the presence of intrinsic correlations. We also concluded that such trains show strong relation with the registration time as they are most likely to appear right after the user joined the network. High activity bursty peaks which evolved later and even in multiple times were also detected for some users. We showed that such patterns are correlated with user activity and free service usage and could be triggered by free and paid service adoption. The observed temporal behaviour and non-trivial correlations disclose characteristics about the evolution of social networks which suit well into the general picture of human dynamics as correlations and heterogeneity were confirmed earlier in many independent cases. However, beyond sophisticating our present assumptions about human behaviour, these results serve a more pragmatic advantage as they may help to improve the design of online services and to make more efficient allocation of shared computational and communication network resources.

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- [1] Backstrom L, Kumar R, Marlow C, Novak J, Tomkins A (2008) Preferential behavior in online groups. In: Proceedings of the international conference on Web search and web data mining, ACM, New York, NY, USA, WSDM '08, pp 117–128, doi:10.1145/1341531.1341549
- [2] Barabási AL (2005) The origin of bursts and heavy tails in human dynamics. *Nature* 435:207–211, doi:10.1038/nature03459
- [3] Chaovalit P, Gangopadhyay A, Karabatis G, Chen Z (2011) Discrete wavelet transform-based time series analysis and mining. *ACM Comput Surv* 43(2):6:1–6:37, doi:10.1145/1883612.1883613
- [4] Eckmann JP, Moses E, Sergi D (2004) Entropy of dialogues creates coherent structures in e-mail traffic. Proceedings of the National Academy of Sciences of the United States of America 101(40):14,333–14,337, doi:10.1073/pnas.0405728101
- [5] Fortunato S (2010) Community detection in graphs. *Physics Reports* 486(3-5):75–174, doi:10.1016/j.physrep.2009.11.002
- [6] Gaito S, Zignani M, Rossi GP, Sala A, Wang X, Zheng H, Zhao BY (2012) On the bursty evolution of online social networks URL <http://arxiv.org/abs/1203.6744>
- [7] Goh KI, Barabási AL (2008) Burstiness and memory in complex systems. *EPL (Europhysics Letters)* 81(1):48,002+, doi:10.1209/0295-5075/81/48002
- [8] Gonçalves B, Perra N, Vespignani A (2011) Modeling users' activity on twitter networks: Validation of dunbar's number. *PLoS ONE* 6(8):e22,656, doi:10.1371/journal.pone.0022656
- [9] Hartigan JA, Wong MA (1979) A k-means clustering algorithm. *JSTOR: Applied Statistics* 28(1):100–108
- [10] Holme P, Saramäki J (2012) Temporal networks. *Physics Reports* In press, doi:10.1016/j.physrep.2012.03.001
- [11] Jo HH, Karsai M, Kertész J, Kaski K (2012) Circadian pattern and burstiness in mobile phone communication. *New Journal of Physics* 14(1):013,055+, doi:10.1088/1367-2630/14/1/013055
- [12] Karsai M, Kivelä M, Pan RK, Kaski K, Kertész J, Barabási AL, Saramäki J (2011) Small but slow world: How network topology and burstiness slow down spreading. *Physical Review E* 83(2):025,102+, doi:10.1103/PhysRevE.83.025102
- [13] Karsai M, Kaski K, Barabási AL, Kertész J (2012) Universal features of correlated bursty behaviour. *Scientific Reports* 2:397, doi:doi:10.1038/srep00397
- [14] Karsai M, Kaski K, Kertész J (2012) Correlated dynamics in egocentric communication networks URL <http://arxiv.org/abs/1202.3062>
- [15] Kivelä M, Pan RK, Kaski K, Kertész J, Saramäki J, Karsai M (2012) Multiscale analysis of spreading in a large communication network. *Journal of Statistical Mechanics: Theory and Experiment* 2012(03):P03,005+, doi:10.1088/1742-5468/2012/03/P03005
- [16] Kovanen L, Karsai M, Kaski K, Kertész J, Saramäki J (2011) Temporal motifs in time-dependent networks. *Journal of Statistical Mechanics: Theory and Experiment* 2011(11):P11,005+, doi:10.1088/1742-5468/2011/11/P11005
- [17] Krings G, Calabrese F, Ratti C, Blondel VD (2009) Urban gravity: a model for inter-city telecommunication flows. *Journal of Statistical Mechanics: Theory and Experiment* 2009(07):L07,003+, doi:10.1088/1742-5468/2009/07/L07003
- [18] Krings G, Karsai M, Bernharsson S, Blondel VD, Saramäki J (2012) Effects of time window size and placement on the structure of aggregated networks. *EPJ Data Science* 1(1):4, doi:10.1140/epjds4
- [19] Leskovec J, Backstrom L, Kumar R, Tomkins A (2008) Microscopic evolution of social networks. In: Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining, ACM, New York, NY, USA, KDD '08, pp 462–470, doi:10.1145/1401890.1401948
- [20] Lin J, Keogh E, Lonardi S, Chiu B (2003) A symbolic representation of time series, with implications for streaming algorithms. In: Proceedings of the 8th ACM SIGMOD workshop on Research issues in data mining and knowledge discovery, ACM, New York, NY, USA, DMKD '03, pp 2–11, doi:10.1145/882082.882086
- [21] Lin J, Keogh E, Wei L, Lonardi S (2007) Experiencing sax: a novel symbolic representation of time series. *Data Min Knowl Discov* 15(2):107–144, doi:10.1007/s10618-007-0064-z
- [22] Malmgren RD, Stouffer DB, Motter AE, Amaral LAN (2008) A poissonian explanation for heavy tails in e-mail communication. Proceedings of the National Academy of Sciences 105(47):18,153–18,158, doi:10.1073/pnas.0800332105
- [23] Milo R, Shen-Orr S, Itzkovitz S, Kashtan N, Chklovskii D, Alon U (2002) Network motifs: Simple building blocks of complex networks. *Science* 298(5594):824–827, doi:10.1126/science.298.5594.824
- [24] Miritallo G, Moro E, Lara R (2011) Dynamical strength of social ties in information spreading. *Physical Review E* 83(4):045,102+, doi:10.1103/PhysRevE.83.045102
- [25] Onnela JP, Saramäki J, Hyvönen J, Szabó G, Lazer D, Kaski K, Kertész J, Barabási AL (2007) Structure and tie strengths in mobile communication networks. Proceedings of the National Academy of Sciences 104(18):7332–7336, doi:10.1073/pnas.0610245104
- [26] Albert R, Barabási AL (2002) Statistical mechanics of complex networks. *Reviews of Modern Physics* 74:47–97, doi:10.1103/RevModPhys.74.47
- [27] Rybski D, Buldyrev SV, Havlin S, Liljeros F, Makse HA (2009) Scaling laws of human interaction activity. Proceedings of the National Academy of Sciences 106(31):12,640–12,645, doi:10.1073/pnas.0902667106
- [28] Stehlé J, Barrat A, Bianconi G (2010) Dynamical and bursty interactions in social networks. *Physical Review E* 81(3):1–5, doi:10.1103/PhysRevE.81.035101